Effort in Phone Survey Response Rates: The Effects of Vendor and Client-Controlled Factors

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This article presents a model using data from 205 telephone surveys conducted in the same survey lab over a three-year period. The model demonstrates that while response rates are partly a function of variables reflecting effort, they are also affected by contextual variables often not under the survey vendor's control. Significant factors that affected response rates included the salience of the survey to the population, the survey length, the type of sample (listed vs random-digit dialing), minutes per piece of sample (effort), and the amount of time the survey was in the field. A ten-minute increase in survey length results in a 7% decrease in the response rate. An increase of one day in the field per one hundred cases (fielding time) results in a 7% increase in the response rate. An increase of one interviewer minute devoted to each piece of sample released results in a 2.2% increase in overall response rates and a 3.4% increase in random-digit dialing response rates.

Keywords: *response rate; survey; effort; nonresponse*

Since 1946, response rates have been used to gauge the nonresponse bias and nonresponse error associated with surveys (Hansen and Hurwitz 1946). Since then, much has been written about nonresponse, resulting in extensive literature on how to reduce nonresponse (Dillman 1978; Kristal et al. 1993; Piazza 1993; Brehm 1994; Roth and BeVier 1998; Pickery, Loosveldt, and Carton 2001; Tuckel and O'Neill 2002) and how to adjust for it (Alho 1990; Park and Brown 1994; Copas and Farewell 1998; Colombo 2000). This research has contributed enormously to maintaining high response rates when the overall trend is for them to decline. More recent research has shown that the effect of nonresponse on data is less critical than previously thought (Curtin, Presser, and Singer 2000; Keeter et al. 2000). This helps put response rates in

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perspective and reduces the tendency to disregard survey research simply because of low response rates. Attempts to standardize disposition codes and response-rate formulas have resulted in increased comparability across surveys when the survey methods are the same (Lynn et al. 2002; Smith 2002).

This article is not about the causes of nonresponse, reducing nonresponse, or how nonresponse affects data. Instead, we focus on the relationship between survey effort expended and response rates. Clients often complain about low response rates, suggesting that a low response rate indicates low survey vendor effort. While a definite correlation exists between survey effort and response rates, variables unrelated to effort strongly affect response rates as well. This article is an attempt to show that, depending on the particular contribution of all these variables, response rates may be low even after high effort.

Virtually all other studies about nonresponse and response rates use respondents as observations. In this study, the observations are surveys. As a result, the sample size for this study is much smaller than most studies concerning nonresponse, and several variables do not have the range typically found in those studies. The data set in this article is ideal for testing the effect of effort versus noneffort variables on response rates.

BACKGROUND

A response rate is broadly defined as the proportion of all eligible cases that result in complete interviews. The critical question is, What counts as an eligible case? As the circumstances under which surveys are conducted vary greatly, so does the definition of an "eligible" case. Therefore, response rates cannot be calculated with a single formula. The American Association for Public Opinion Research (AAPOR 2000) recognizes this and offers six response-rate formulas, RR1 to RR6, that involve different definitions of what counts as an eligible case and what counts as a complete interview. By sanctioning these formulas, the AAPOR encourages researchers to choose the one most appropriate for their work. The RR1 formula is used in the current study.

The result, however, is that response rates can vary greatly depending on which formula is applied to a set of data, and this has had serious consequences for the survey research industry. Response rates have dropped over time, yet some clients still expect the higher rates more common in previous decades. Some survey researchers respond by choosing the response-rate formula that puts their work in the best possible light.

This can lead to a vicious cycle. Some researchers report very high response rates (whether using the formula that is most appropriate for their particular survey or not)—in some cases, as high as 70% or more. Survey clients and journal editors, seeing these high response rates, demand similar response rates for surveys they contract or in articles reporting survey results. Researchers may then be inclined to respond by adjusting survey parameters, disposition codes, or response-rate calculations to report higher rates. This perpetuates the cycle by reinforcing the idea that very high response rates are the norm and are achievable regardless of the survey design.

The problem of inflated response-rate reporting is exacerbated when state and federal agencies enshrine specific response-rate levels as an industry standard. For example, a 1979 memo from the director of the U.S. Office of Management and Budget to heads of executive departments and agencies said,

> It is expected that data collections based on statistical methods will have a response rate of at least 75 percent. Proposed data collections having an expected response rate of less than 75 percent require a special justification. Data-collection activities having a response rate of under 50 percent should be terminated. Proposed data-collection activities having an expected response rate of less than 50 percent will be disapproved.

This memo did not discuss the method for calculating response rates, nor did it discuss the survey mode (mail, telephone, or face to face) or the population to be surveyed. It also stated that proposed surveys that required more than an hour of a respondent's time would be disapproved.

Personal communication between one of the authors and Office of Management and Budget staff revealed the Office of Management and Budget does not currently use these 1979 published rates as official guidelines. Rather, it recognizes response rates as one of many important factors to consider in evaluating data quality. Several authors have made this point, suggesting that other variables, such as nonresponse bias, are more important than response rates (Groves 1989; Krosnick 1999; Biemer and Lyberg 2003). Nevertheless, some consumers of survey research still evaluate data quality using fixed response-rate levels and feel cheated if results fall below the so-called industry standard. In our own lab, we have had clients complain that a 50% response rate on an random-digit dialing (RDD) survey indicated cost cutting or poor execution. As Curtin, Presser, and Singer (2000) and Keeter et al. (2000) have shown, a high response rate does not guarantee reliable data, particularly when response rate calculations and case-coding schemes vary.

Many contextual variables must also be considered when researchers and clients make decisions based on survey results.

For example, the public regularly consumes data gathered from polls fielded for only a few days, such as political polls designed to be snapshots of quickly changing public opinion. These time-limited polls often yield very low response rates, yet they influence many groups, from politicians to investors and others, who make decisions based on their results. And, as past elections have shown, they are often good predictors of electoral outcomes despite the low response rates. Although polls have a different goal than most other survey research, they represent the opposite extreme of trading low response rates for something else, in this case, a quick snapshot of public opinion.

Survey researchers who conduct surveys for the Behavioral Risk Factor Surveillance System (BRFSS) for many U.S. states often struggle to achieve a 50% response rate. Yet every year, articles appear in well-respected journals using the BRFSS results (see Foster et al. 2003; Nelson et al. 2003; Carpenter 2004; Strine et al. 2004). The enormous value of the data and the size of the coverage area outweigh the low response rates. Clearly, we encounter situations in which we are still willing to use survey results despite low response rates.

The main concern of this article is how some consumers of survey research use response rates as a measure of survey effort. These consumers are concerned not only about how representative their data are but also whether the survey vendor gave them the effort for which they paid. We will demonstrate that while response rates do rise and fall with variables associated with effort, they can also rise and fall dramatically because of variables typically not under the survey vendor's control. It is important to point out that consumers of survey research should be more concerned about survey nonresponse rather than response rates alone. However, given the focus by editors and clients on response rates, that is the focus of this article.

For the purposes of this article, we divide the survey community into two groups. Survey clients pay for surveys and are most invested in well-conducted surveys. Survey vendors perform the surveys and receive the funds and presumably have an incentive to finish the work under contract cost. In some cases, the survey client is also the vendor, typically where a consulting company or an academic survey has received grant funding to perform a survey as part of a research project. Even in such cases, grant program officers may also be considered clients.

THE VARIABLES

When contracting with a survey vendor for a telephone survey, many clients specify one or more of the following:

1. maximum call attempts,
2. maximum number of refusal callbacks,
3. time frame for running the study, and
4. rotation of calls across day of the week and time of day.

The existence of a contract does not guarantee that a survey vendor will be able to strictly adhere to its obligations. Given time and money constraints, some cases may be left unfinalized and others may not be rotated properly across days and times. In other words, all samples may not be worked to the extent stipulated in the contract. Failure to work the sample according to the contract may translate into a lower response rate.

Other factors that can affect a response rate are often not under the control of the survey vendor. These include

5. the population surveyed,
6. survey length,
7. sample quality,
8. listed versus RDD, and
9. salience of the survey topic to respondent.

Variations in these factors can, and often do, result in higher or lower response rates. Consider two very different cases. The first is a telephone survey of Medicaid clients assigned to a pilot program that attempts to control costs by limiting the number of brand-name prescriptions covered. The second is an RDD survey of U.S. households concerning current economic trends. Even if the factors under the survey vendor's control are executed in the same way, one should not expect the response rates to be the same.

METHOD

We present data on response rates for 205 surveys conducted at the University of Florida Survey Research Center at the Bureau of Economic and Business Research between January 2000 and July 2004 and test the effect of several variables on those response rates. We eliminated surveys of businesses, surveys of adolescents in which the parents had been preinterviewed and had provided approval, and surveys in which respondents actually called us. All surveys on our final list are studies in which our interviewers called the respondent, the respondent lived in a household, and the potential respondent was not selected through any prescreening process.

As far as we are aware, this is the only report of response rates for telephone surveys across several different surveys in a single lab, although attempts have been made to isolate factors that affect response rates in mail surveys (Heberlein and Baumgartner 1978). Standardization of lab practices across surveys acts as a control for many potentially intervening variables, making it possible to isolate the effect of particular variables on response rates. By the same token, we recognize that the practices of one survey lab may not be generalizable to other labs.

Most computer-assisted telephone interviewing (CATI) software today operates as a relational database and includes an attempt database with one record per call attempt. Typically, such a record contains the date and time of the call and its disposition. Assuming the use of standard AAPOR disposition codes, we can use this database to calculate the following variables.

- Number of calls per case: a measure of call attempts. Many cases are finalized, one way or the other, with a single call. A proper measure of effort is the extent to which the survey vendor pursues cases that are still eligible. This is reflected in the average attempts for cases in which the most recent disposition is an eligible disposition. Eligibility was defined using AAPOR definitions of eligible dispositions (see Table 1). For example, a case coded as an Answering Machine (AAPOR codes 2221, 2222, and 3140) on all attempts would be considered in this measure. On the other hand, a case coded as a No Answer (AAPOR code 3130), then later as a Disconnected Number (AAPOR code 4320), would not count as it was ultimately determined to be ineligible.
- Minutes per piece of sample: calculated by dividing the total number of interviewer minutes by the total sample released. It is different from fielding time because a survey could be fielded over many days but have few resources devoted to it. Higher numbers indicate more resources devoted to each case. To reduce the relationship between this variable and survey length, we removed the time of the actual call where a completed interview was coded. Although the variable is still correlated with survey length, the correlation is much less.
- Refusal calls: the average number of calls beyond a refusal for cases that have a refusal in their history.
- Survey length: the average number of minutes per completed interview. It is calculated on the sum of time spent on a case disposed as complete, as opposed to the calls that led up to its being a complete. If the substantive interview took more than two calls, then the time for both calls is summed.
- Fielding time: calculated by dividing the number of working days in the field by the total number of cases released. It is a measure of field time normalized by the size of the sample. Higher numbers reflect more field time. We included a square of this variable to account for a possible curvilinear relationship. It is important to keep in mind that the mean of this variable is quite small since as a

TABLE 1
Eligibility of Standard American Association for Public Opinion Research (AAPOR) Disposition Codes

AAPOR Disposition Description	AAPOR Disposition Code	Eligibility
Completed interview	1100	E
Partial interview	1200	E
Strong refusal	2110	E
Soft refusal	2120	E
Respondent never available	2210	E
Answering machine, message	2221	E
Answering machine, no message	2222	E
Dead	2310	E
Physically, mentally unable	2320	E
Language unable	2330	E
Miscellaneous unable	2340	E
Busy	3120	E
No answer	3130	E
Answering machine, don't know if household	3140	E
Technical phone problem	3150	E
Temporary phone problem	3151	E
Fax/data line	4200	I
Nonworking number	4310	I
Disconnected number	4320	I
Number changed	4430	I
Cell phone	4410	I
Call forwarding	4420	I
Business/government/other organization	4430	I
Institution	4520	I
Group quarters	4530	I
No eligible respondent	4700	I
Quota filled	4800	I
Callback, respondent not selected	5100	E
Callback, respondent selected	5200	E

NOTE: E = eligible; I = ineligible.

proportion of a 24-hour day, a single case does not account for much time. On average, across the 205 surveys, a single case was fielded for a total of approximately 17 minutes.

We also created the following two variables we assumed would affect response rates:

- Salience: a subjective variable assigned by the authors for each survey. It has three values. A value of 1 was assigned for surveys of the general popula-

TABLE 2
Summary Statistics for Independent Variables

	Overall		Listed		Random-Digit Dialed	
Study	M	SD	M	SD	M	SD
Number of calls per case	9.2	4.8	8.9	5.2	9.4	4.1
Minutes per piece of sample	5.8	3.7	6.7	4.2	4.4	1.9
Refusal calls	3.6	1.78	3.9	1.97	3.1	1.31
Survey length (minutes)	20.8	15.16	22.5	18.3	18	7.53
Fielding time per sample	0.012	0.029	0.016	0.035	0.005	0.011
Fielding time squared	0.001	0.006	0.001	0.007	0.0001	0.0008
Salience2	0.15		0.18		0.11	
Salience3	0.45		0.61		0.21	
Sample	0.39					

NOTE: The variables salience and listed versus random-digit dialed are categorical dummy variables.

tion ($n = 82$). A value of 2 was assigned for surveys of a subpopulation ($n = 31$). A value of 3 was assigned if the subpopulation surveyed were members of a program being evaluated; that is, they may feel they would benefit directly from participating in the survey ($n = 92$). An RDD survey of those 65 years and older would be coded 2 because they are a subpopulation, but if they were part of a programmatic group reflected in the survey questions, such as Medicare, the survey would be coded as a 3. This was represented in the regression as two dummy variables. For listed surveys, 61% had a salience of 3, whereas only 20% of RDD surveys had a salience of 3.

- RDD or listed: a value of 0 indicates a listed sample ($n = 125$), and a 1 indicates RDD ($n = 80$). This variable was excluded for the analysis by sample type.

We used these variables in a regression model to predict RR1 response rates on the 205 surveys. Summary statistics for these variables are given in Table 2. RR1 is the most conservative of the six AAPOR response rates for telephone surveys. The formula for RR1 is

$$\text{RR1} = \frac{I}{(I + P) + (R + NC + O) + (UH + UO)},$$

where

I = complete interview
P = partial interview
R = refusal and break off

NC = noncontact
O = other
UH = unknown if household/occupied housing unit
UO = unknown, other

We included two additional variables in the first pass at the analysis: average number of different days of the week each case was called and average number of different hours of the day each case was called. Both of these variables were highly correlated with the number of calls for eligible cases and were dropped from the regression. Several remaining variables were correlated but not to such an extent that would justify their elimination from the model.

Another variable that could be important for RDD surveys is respondent selection. In our case, most RDD surveys used the youngest male/oldest female method. Exceptions were a handful of health care surveys in which we asked for the person most knowledgeable about health care decisions. Given the uniformity of the method for selecting a respondent in this data set and our focus on survey effort, we did not include it as a variable.

RESULTS

Table 3 shows the results of three regression models using these variables to predict the RR1 response rate calculated for each survey. Table 4 shows the effect at the mean of the variable on the response rate. This was calculated by multiplying the regression coefficient by the mean of the variable. The overall model includes the variable sample (whether the study used listed or RDD sample) as a variable, in which the remaining models calculate the same regression for listed versus RDD. The overall model was very significant, with an R^2 of .52. As would be expected, we saw a dramatic difference in the fit of this model between listed and RDD surveys.

To test the fit of the model, we performed a Hosmer-Lemeshow test and a Pregibon's Link test. Both tests would have a significant test statistic if the model did not show good fit. Both tests provided strong evidence of good fit, $F(5, 200) = 0.76$, $p = .58$; t statistic = 0.01, $p = .99$.

For fielding time, we included the square as an additional variable. This makes sense for this variable as it could yield diminishing returns (see Goyder 1985). By including this transformation, we can identify diminishing or increasing returns.

The overall model demonstrates a good fit with a relatively low proportion of the variance explained ($R^2 = .52$). We calculated the overall model

TABLE 3
Variables in Model Used to Predict Response Rate Across 205 Surveys

	Overall ($R^2 = .52$)		*Listed Sample* ($R^2 = .42$)		*Random-Digit Dialed Sample* ($R^2 = .67$)	
Variable	*Coefficient*	*Probability* > t	*Coefficient*	*Probability* > t	*Coefficient*	*Probability* > t
Constant	0.327	0.000	0.425	0.000	0.096	0.024
Salience level 2	–0.783	0.030	–0.177	0.000	0.019	0.549
Salience level 3	0.066	0.007	–0.002	0.946	0.082	0.018
Number of calls per case	0.001	0.776	0.0008	0.870	0.003	0.643
Minutes per piece of sample	0.022	0.001	0.017	0.041	0.034	0.007
Refusal calls	0.005	0.592	0.0002	0.989	0.013	0.447
Survey length	–0.007	0.000	–0.006	0.000	–0.005	0.059
Fielding time	7.078	0.000	5.198	0.007	17.258	0.005
Fielding time squared	–23.965	0.003	–16.227	0.067	–147.511	0.042
Listed versus random-digit dialed	–0.118	0.019	NA	NA	NA	NA

NOTE: NA = not applicable.

TABLE 4
Coefficients at the Means

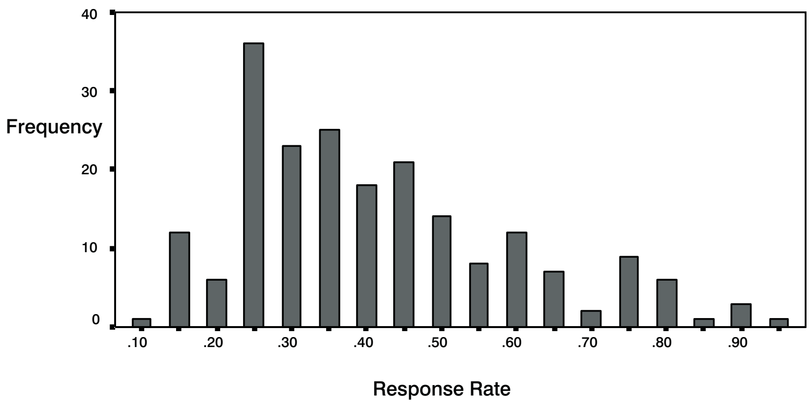
	Coefficient × Mean		
Study	*Overall*	*Listed*	*Random-Digit Dialed*
Number of calls per case	0.01	0.01	0.03
Minutes per piece of sample	0.13	0.11	0.15
Refusal calls	0.02	0.00	0.04
Survey length (minutes)	–0.15	–0.14	–0.09
Fielding time per sample	0.085	0.083	0.086
Fielding time squared	–0.024	–0.016	–0.015
Salience level 2	–0.12	–0.03	0.00
Salience level 3	0.03	0.00	0.02
Sample	–0.05		

because, in our experience, many clients do not make the distinction between sample type, even though most survey researchers do. By breaking out the model between listed versus RDD surveys, we see that these variables account quite well for the variance in response rates for RDD surveys. For listed surveys, which vary more in population and design, a larger portion of variance in the response rate remains unaccounted for.

Survey salience appears to have some impact on response rates for listed and overall samples. For the overall and listed samples, this variable is significant for the first level of salience that distinguishes between respondents from the general population and those within some subpopulation. For the RDD sample, this variable is significant for the second level of salience that identifies people who are members of a program that is being evaluated.

For the overall and listed samples, fielding time is significant. This variable is reported as days in the field per piece of sample, on average 0.012 days (about seventeen minutes) per case for this data set. The square of this variable is also significant and the coefficient negative, indicating that longer fielding times have decreasing returns. In the survey industry, it is well known that the longer a survey is fielded, the better the response rate. For the overall and RDD samples, there is a point at which fielding time does not increase response rates. The fielding time is sometimes under the vendor's control but is often determined by a combination of deadlines and delivery of sample from clients. Clients who impose short fielding times by virtue of their deadlines or delivery of sample delays should be aware of the effect on response rates.

FIGURE 1
Distribution of Response Rates, All Surveys



The fielding time squared is significant as well for RDD, listed and overall. Note that the coefficient on all three variables is negative, suggesting that there is a threshold beyond which the gains from additional fielding time are decreasing. In other words, additional fielding time does increase response rates, up to a point. The threshold will be different depending on the survey.

Survey length is significant for the overall, listed, and RDD samples, suggesting the longer a survey, the lower the response rate. Although the variable "Sample*Survleng" was not included in the final analysis, its significance in the overall model confirms that survey length behaves differently depending on the type of sample.

Minutes per piece of sample is significant for all three samples. We saw diminishing returns to response rate as minutes per piece of sample increased. This variable is the purest measure of the effort expended by a survey vendor and is usually under survey vendor control. It appears that for listed-sample surveys, other factors, apparently not represented in the model, tend to determine the response rate. For RDD surveys, minutes per piece of sample is an excellent measure of the effort a vendor expended to get a higher response rate.

Pursuit of eligible cases as measured by the number of calls per case is surprisingly insignificant. The number of times a case is called when its most recent disposition is eligible is controlled and paid for by the survey vendor. This effect is apparently accounted for by other variables.

FIGURE 2
Distribution of Response Rates, Listed Sample Surveys

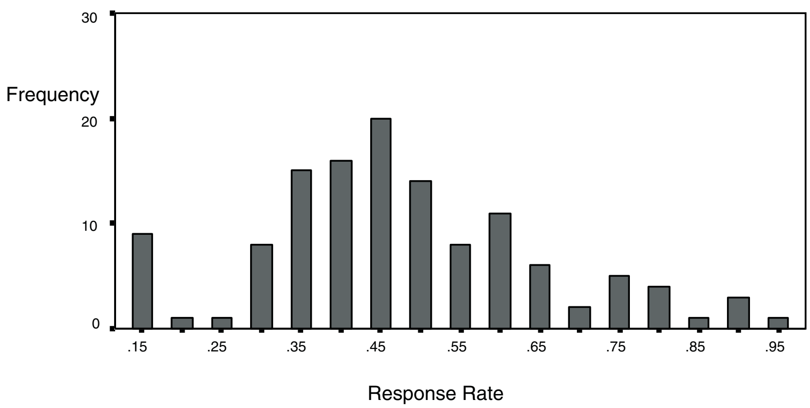
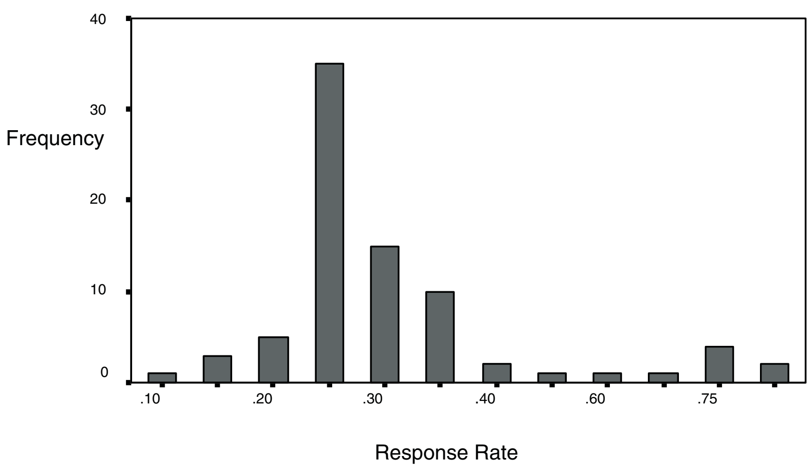


FIGURE 3
Distribution of Response Rates, Random-Digit Dialing Surveys



Similarly, the extent to which refusals are pursued beyond the first refusal does not significantly affect the response rate across either listed or RDD surveys. We have not discussed surveys that used both letters and incentives as these variables had low sample size. A histogram of the response rates for all studies used here is included in Figure 1 and is broken out for listed (Figure 2) and RDD (Figure 3).

DISCUSSION

In the above analysis, we identified several variables that affect response rates. Many have already been identified as affecting response rates by previous research. However, most prior research has been limited to mail surveys, and none have examined these variables together across a large number of surveys.

Nonresponse is a function of many factors, and consumers of survey research are well advised to evaluate surveys individually, taking all such variables into account and balancing the potential benefits of the research against the possible consequences of nonresponse. In other words, a minimum acceptable response rate that can be applied to all surveys does not exist.

Survey research is unusual compared to other academic disciplines because it has well-defined academic and commercial components. It is both a science of human behavior and a retail enterprise. Although the retail aspect of survey research benefits from the academic side, they are often at odds. The commercial aspect of survey research creates pressures to disregard academic findings that are costly to implement, with cost being a key factor in remaining competitive for both purely commercial as well as grant-funded research. It is difficult to imagine any other academic area that is in such a position of serving two masters.

These findings would be of particular interest to editors and clients who currently use response rates as a measure of effort. Although effort influences response rates, this study shows response rates are also greatly affected by contextual variables not under survey vendor control. Thus, editors and clients should be cautious about rejecting research that does not meet a minimum response rate because of concerns about low vendor effort.

For what should a survey vendor be held accountable? Certainly, an important factor that is largely under the vendor's control is the number of minutes per piece of sample, particularly for RDD surveys. This will vary depending on the circumstances of the survey, just like response rates. However, if in addition to reporting response rates, survey vendors reported the average number of minutes expended per case, editors and clients would have a better indication of effort.

Fielding time, as expressed by days in the field per piece of sample, accounts for a large proportion of the variability in response rates. Reporting this number and indicating the time frame within which the survey was conducted would also allow consumers to assess fairly whether a given response rate is within industry standards. If nothing else, clients should be aware of the consequences of imposing compressed timelines on a survey.

One reviewer suggested using the AAPOR response-rate calculator (on their Web site) to calculate some of these variables and provide the results to the survey sponsor as a way of documenting effort. This is problematic, as the response-rate calculator uses a data set with one observation per phone number. Instead, we propose putting an additional calculator on the AAPOR Web site that uses as input the attempt file collected by most CATI systems. This file would have one observation per call attempt, and the program could calculate variables such as fielding time and minutes per piece of sample from this file, as we have for this article.

If a client or editor uses the results of a survey to evaluate the survey vendor, the response rate alone can provide only part of the picture. Admittedly, some survey vendors do not expend enough effort on their surveys. However, consumers of survey research risk dismissing valuable research based on impressions created by incomplete information. We believe if survey vendors made a concerted effort to educate consumers, clients, and editors, including providing them with measures of effort, we may be able to positively change the current culture of survey evaluation. Ultimately, those conducting the survey must let clients know how the constraints they impose on projects may affect response rates.

For those interested in analyzing these data for themselves, they are available in a variety of formats. Please contact the lead author to request the data.

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